

**TITLE: ADVANCED ENGINE CONTROL FOR INCREASING FUEL EFFICIENCY AND  
POWER DENSITY WHILE REDUCING OBSERVABLE EMISSIONS FROM MILITARY  
DIESEL ENGINES**

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**SUMMARY:**

Military diesel engines used in combat and tactical applications have their own specific engine control requirements that differ from those of commercial heavy-duty vehicles. The implementation of advanced engine control methods in diesel-powered military vehicles can result in an increase in their performance, a reduction in their fuel consumption, a reduction in their observable exhaust emissions and an improvement in their stealth capabilities. Neural network-based engine control has the potential to allow for the simultaneous, optimized control of several engine parameters such as fueling quantity, injection timing, injection pressure and turbocharger boost pressure. Future engines will be considerably more complicated in their control, incorporating such additional technologies as exhaust gas recirculation, variable geometry turbocharging, variable valve timing, multiple injection strategies and exhaust gas aftertreatment. The advanced engine control techniques developed here will facilitate the optimal control of these more sophisticated engines in future military applications.

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**TECHNICAL DISCUSSION:**

Modern military diesel engines used for transportation, tactical and combat vehicle propulsion, and power generation are mostly direct injection, four-stroke, turbocharged, aftercooled engines, derived typically from commercial versions of the same engines. However, in terms of their control, military engines have specific requirements that are not adequately addressed in commercial vehicle applications. It would offer a significant strategic advantage under battlefield conditions if these engines offered improved power density (for increased performance), reduced fuel consumption (to increase vehicle range and to reduce refueling requirements), and reduced observable exhaust emissions (to improve their stealth capabilities). These advances can be realized through sophisticated engine management that interfaces with the electronically controlled injection systems present on modern day diesel engines. Moreover, such advanced management will prove essential in optimizing the technology-laden camless diesel engines of the future.

## REPORT DOCUMENTATION PAGE

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This present work is aimed at the development of artificial neural network (NN)-based techniques for the control of military diesel engines. Artificial NNs attempt to mimic human pattern recognition abilities, with the capacity to learn the associations between given inputs with respect to desired outputs, provided a sufficient amount and scope of data are supplied.

West Virginia University and NeuroDyne, Inc. have demonstrated the efficacy of a NN-based engine modeling system that employs a recurrent neural network structure with error backpropagation. The software, designed by NeuroDyne, Inc., uses three layers and a moving history of information at previous time steps to predict exhaust emissions levels, on-line in real time. The engine modeling or virtual sensor system consists of a predictive engine model (or models) designed to run on a microprocessor in parallel with the engine in real time, taking input signals from the same sensors as the engine itself. The NN model of the engine is able to make highly complex, non-linear and multi-dimensional associations between selected input parameters and outputs in real-time, which allows accurate predictions of engine performance across the full range of engine operation. In compression ignition engines, the NN model takes as inputs the manifold air pressure (MAP) and temperature (MAT), engine speed, engine coolant temperature (ECT), engine oil temperature (EOT), exhaust gas temperature (ExT), injection pressure (ICP), start of injection (SOI), fuel injection pulse width (FIPW), and commanded fueling rate (APS) as a function of time. The NN model of the engine is able to predict real-time torque output [TQ], engine exhaust emissions (unburned hydrocarbon [HC], carbon monoxide [CO], oxides of nitrogen [NO<sub>x</sub>], and particulate matter [PM] or exhaust opacity [OP] smoke emissions), and fuel consumption (from CO<sub>2</sub> emissions) across the full range of engine operation.

During limited dynamometer testing, the NN model learns in real-time and on the fly the precise relationship between all designated inputs and outputs. The NN model assigns global or general weights among all designated inputs (engine operating parameters) and corresponding outputs (torque, fuel consumption, and regulated emissions) based on results learned during engine dynamometer testing. The required breadth of training is on the order of a few hours of highly transient testing. A further (local) set of weights can be allowed to vary in time across the life of the engine in the field, thereby providing a true learning, adaptive prediction system. The resulting NN submodels are able to provide the apparent results from a virtual suite of emissions sensors to the driver, to a smart diagnostic system, or to an engine controller. These virtual sensor results may either be unmeasured or unmeasurable engine parameters, or a duplicate estimation of already measured variables. One immediate application is in the virtual measurement of engine-out NO<sub>x</sub> emissions for on-board diagnostics (OBD).

The first year project goals of procuring a heavy duty diesel engine, conducting dynamometer testing for the neural network input, modifying an existing neural network code for the diesel engine, and validating the prediction capabilities of the neural network models with blind data sets have been completed and some of the prediction results are shown below. The (blind) prediction of the emissions from a Navistar T444E direct injection, turbocharged diesel engine measured over the Federal Test Procedure, using limited dynamometer testing to train the NN, is shown to be excellent, and well within the accuracy of the emissions measurement equipment.

The application of the NN-based submodels to predict and control the emissions and torque from a heavy-duty diesel engine to minimize black smoke emissions will be discussed. The continued development of a NN-based emissions predictions system using the existing engine sensors will also be discussed. Applications of the NN-based system as an alternative to map-based engine control, as a diagnostic method and for off-line emissions prediction will be presented. Optimization of the virtual sensing technique to allow high power density operation while minimizing black smoke will also be discussed.

Table 1: Neural Network Engine Model Input and Output Variables

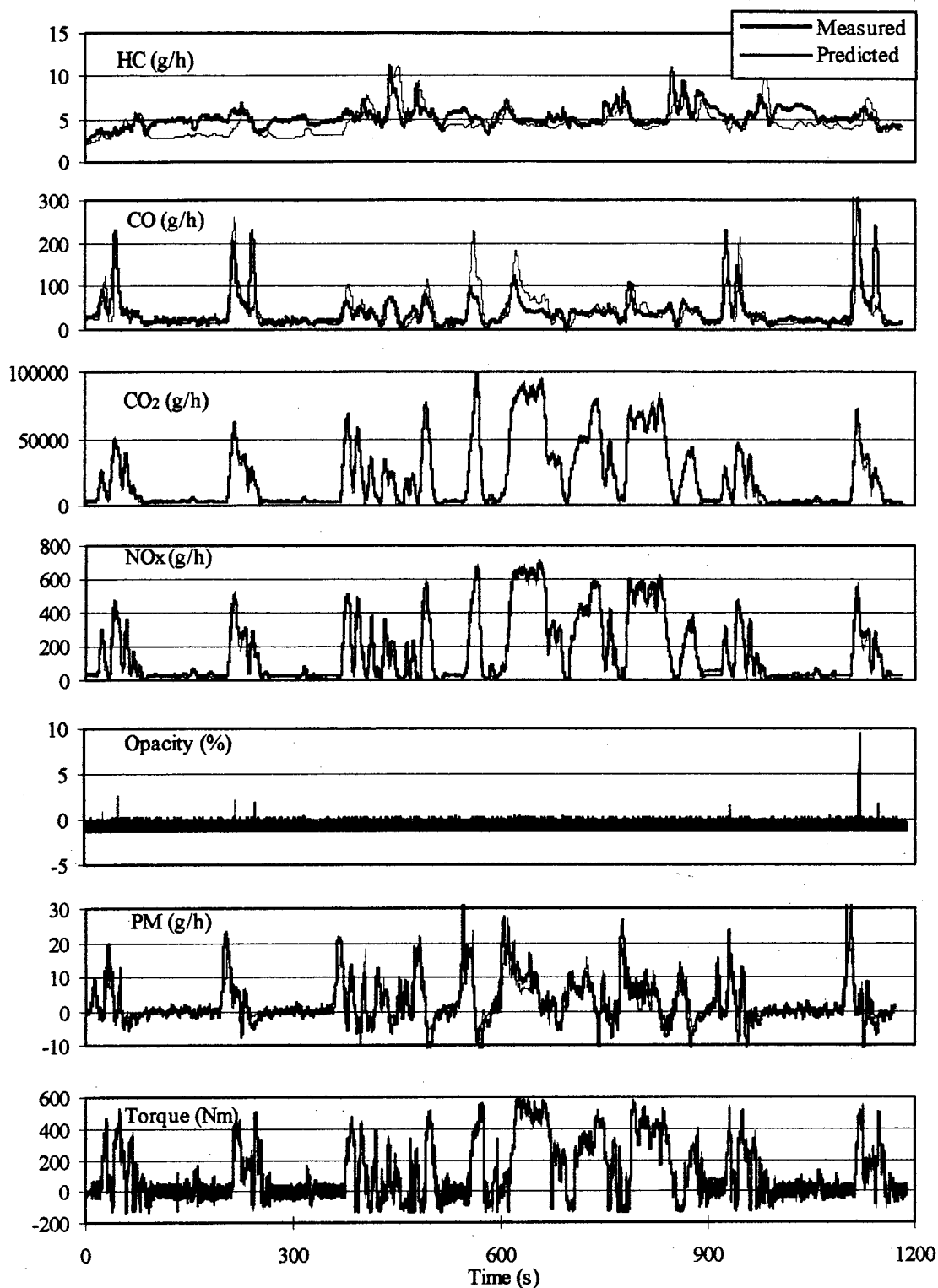
	Neural Network Submodel Name							
	Gaseous Emissions		Particulate Matter		Exhaust Opacity		Output Torque	
	EM		PM		OP		TQ	
	input	output	input	output	input	output	input	output
APS (%)	x		x		x		x	
SOI ( $10^{-6}$ s)	x		x		x		x	
FIPW ( $10^{-6}$ s)	x		x		x		x	
ICP (ADC)	x		x		x		x	
MAP (kPa)	x		x		x		x	
ECT (°C)	x		x		x			
EOT (°C)	x		x		x			
ExT (°C)	x		x		x		x	
IAT (°C)	x		x		x		x	
Speed (rpm)	x		x		x		x	
Torque (ft-lbf)								x
HC (g/h)		x						
CO (g/h)		x						
CO <sub>2</sub> (g/h)		x						
NOx (g/h)		x						
PM (g/h)				x				
OP (%)						x		

Table 2: Neural Network Architecture for each Submodel.

NN Feature	EM	PM	OP	TQ
Number of Inputs	10	10	10	8
Number of Nodes in 1 <sup>st</sup> Hidden Layer	15	15	15	15
Number of Nodes in 2 <sup>nd</sup> Hidden Layer	5	5	-	-
Number of Outputs	4	1	1	1

Table 3: Neural Network Engine Model Prediction Error versus Measurement Error.

Output Parameter	Measurement Error	Measurement Error (%)	NN Virtual Sensor Error	NN Virtual Sensor Error (%)
Torque (ft-lbf)	23.21	4.38	24.75	4.67
HC (g/h)	0.47	1.17	1.50	3.76
CO (g/h)	16.58	1.04	24.12	1.51
CO <sub>2</sub> (g/h)	1648	1.50	2219	2.02
NOx (g/h)	14.91	1.86	25.81	3.31
PM (g/h)	3.09	4.41	2.69	3.85
OP (%)	0.48	2.26	0.47	2.24



**Figure 1: Predicted versus Measured Performance and Emissions from a Navistar T444 Direct Injection Engine, as tested over the FTP.**